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Optimization Algorithm for Group Consensus Reaching in Collaborative Adult Education †

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Abstract

In collaborative adult education scenarios, learners have strong heterogeneity and complex preferences, and it is difficult for traditional consensus-building methods to effectively address the challenges brought about by the expansion of group size and the intensification of opinion differences. In this study, we used a group consensus achievement optimization algorithm (GCAOA) for collaborative adult education to explore different dimensions of learner feature modeling frameworks, design a preference-learning module based on graph attention networks, and combine multi-objective optimization strategies and adaptive adjustment mechanisms to achieve high-quality and efficient group consensus. The experimental results showed that GCAOA is superior to traditional methods in terms of consensus achievement rate, convergence speed, stability, and scalability, with a consensus achievement rate of 93.7%.

Keywords: graph attention network; optimization algorithm; adaptive regulation; preference for learning

1. Introduction

As an essential component of the lifelong learning system, adult education has shown exponential growth in scale and complexity in recent years with the popularity of online learning platforms and the development of the knowledge economy. Collaborative adult education emphasizes the construction of a knowledge system among learners through knowledge sharing, viewpoint collision, negotiation, and discussion [1,2]. It has been extensively studied and proven to significantly enhance learners' cognitive depth and skill transfer ability [3,4], and effective cross-organizational collaboration and networking further strengthen such learning outcomes [5,6]. However, the problem of achieving group consensus in collaborative learning scenarios has long faced three challenges.

1. Challenge of learner heterogeneity: Adult learners exhibit significant differences in cognitive abilities, prior knowledge, occupational background, and learning motivation. This heterogeneity makes it difficult for a single consensus-building strategy to meet the needs of all learners, which can lead to some learners being marginalized or their opinions being systematically ignored.
2. Preference dynamic evolution challenge: In the process of collaborative learning, learners' perspectives and preferences continue to evolve as interactions deepen.

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Static preference modeling methods cannot capture the phenomenon of preference drift, resulting in a deviation between consensus results and learners' real needs [7].

3. Scalability challenge. When the scale of collaborative groups expands from small discussion groups to large online courses with dozens or even hundreds of people, traditional consensus-building algorithms based on pairwise comparisons face exponential computational complexity explosion problems, seriously restricting their practical application value [8].

Previous research has yielded results in the field of group decision-making and consensus building, introducing social network analysis tools to characterize the impact of trust relationships between experts on the consensus process [9,10]. Recently, deep learning techniques have been introduced into the field of preference learning, but research on combining graph neural networks with consensus optimization and specifically adapting them to adult education scenarios is still lacking.

The aim of this study is to design optimization algorithms for the process of reaching group consensus in collaborative adult education, in order to improve decision-making efficiency and fairness. The challenges mainly include significant differences in opinions among adult learners due to their diverse backgrounds, slow convergence of traditional consensus methods, and the need to balance individual preferences with overall group interests. The solution strategy is to quantify the consensus level through mathematical models, introduce iterative feedback mechanisms, dynamically adjust opinion weights and negotiation parameters to minimize consensus costs and accelerate convergence. The expected impact is to improve the decision-making quality and participation satisfaction of collaborative learning, reduce group negotiation time, provide algorithm support for automated negotiation tools on online education platforms, and promote the scientific and intelligent management decision-making of education.

2. Collaborative Adult Education Scene Model

2.1. Characteristics of Learner Groups

The modeling of learner group characteristics in collaborative adult education is a fundamental prerequisite for consensus algorithm design. This study constructs a comprehensive feature vector from three levels: cognitive dimension, social dimension, and motivational dimension, to comprehensively characterize the individual characteristics of learners.

Definition 1 (learner eigenvector)**.** *Let the learner population L = {l1, l2,..., ln}, and the eigenvectors of each learner li are defined as (*Table 1*):*

$$f_i = \left[f_i^{cog}, f_i^{soc}, f_i^{mot} \right] \in \mathbb{R}^{d_f} \tag{1}$$

The cognitive feature sub-vector $f_i^{cog} \in \mathbb{R}^{d_c}$ *includes indicators such as prior knowledge level, learning style preference, and cognitive load tolerance; the social feature sub-vector encodes the social influence, network centrality, and historical interaction activity of learners; the motivational feature sub-vector* $f_i^{mot} \in \mathbb{R}^{d_m}$ *fimot ∈ Rdm quantifies the intrinsic motivation intensity and extrinsic motivation response coefficient.*

In terms of learner authority calculation, we introduce a comprehensive authority index:

$$\alpha_i = \beta_1 \cdot \frac{s_i^{know}}{max_j s_j^{know}} + \beta_2 \cdot \frac{c_i^{central}}{\sum_j c_j^{central}} + \beta_3 \cdot \frac{e_i^{exp}}{T} \tag{2}$$

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Here, s_i^{know} is the knowledge assessment score, $c_i^{central}$ is the network centrality indicator, e_i^{exp} is the years of experience in the relevant field, T is the normalized benchmark for the maximum years of experience, β_1, β_2, and β_3 are weight coefficients that satisfy $\sum k\ \beta_k = 1$.

Table 1. Dimensions and indicator system of learner characteristics.

Dimension	Sub-Dimension	Indicator	Quantification Method	Data Source
Cognitive Traits	Prior Knowledge	Knowledge test scores, educational level	Standardized scoring	Assessment system
Cognitive Traits	Learning Style	VARK questionnaire scores	5-point Likert scale	Survey questionnaire
Cognitive Traits	Cognitive Load	Task completion time, error rate	Behavioral log analysis	Platform logs
Social Traits	Influence	PageRank centrality score	Graph algorithm computation	Collaborative learning records
Social Traits	Activity Level	Average weekly posts, reply rate	Statistical calculation	Platform logs
Motivational Traits	Intrinsic Motivation	Autonomy and competence scores	Self-Determination Theory (SDT) scale	Survey questionnaire
Motivational Traits	Extrinsic Motivation	Point-response coefficient	Behavioral modeling	Platform logs

2.2. Collaborative Learning Behavior

Collaborative learning behavior is the direct driving force behind consensus formation. This study formalizes the collaborative learning process as a weighted directed graph.

Definition 2 (collaborative learning graph)**.** *The collaborative learning graph is defined as G = (L,E,W), where the set of nodes L is the learner population, and the element w_{ij} in the weight matrix $W \in R_n \times n$ reflects the degree of adoption of the learner i's opinion on j. The weight w_{ij} is determined by the collaborative frequency, emotional inclination, and content relevance:*

$$w_{ij}(t) = \gamma_1 \cdot \frac{freq_{ij}(t)}{\sum_k freq_{ik}(t)} + \gamma_2 \cdot sent_{ij}(t) + \gamma_3 \cdot sim_{ij}(t) \quad (3)$$

Here, $freq_{ij}(t)$ is the response frequency within the time window t, $sent_{ij}(t)$ is the positive sentiment strength obtained from sentiment analysis $\in$ [0,1], and $sim_{ij}(t)$ is the cosine similarity of the content. γ_1, γ_2, γ_3 represent weighting coefficient property.

2.3. Definition of Consensus State Space

Definition 3 (individual opinion vector)**.** *For a collaborative learning task containing m discussion topics, the opinion vector of learner li at time t is defined as:*

$$o_i(t) = [o_{i1}(t), o_{i2}(t), \ldots, o_{im}(t)] \in [0,1]^m \quad (4)$$

Here $o_i(t)$ represents the learner's level of identification with the jth topic at time t.

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Definition 4 (group consensus)**.** *The overall consensus of the group at time t is defined as:*

$$CR(t) = 1 - \frac{1}{m}\sum_{j=1}^{m}\frac{1}{n2}\sum_{i<k}|o_{ij}(t) - o_{kj}(t)| \quad (5)$$

When CR(t) $\geq \delta$*, it is considered that the group has reached sufficient consensus.*

Definition 5 (equity indicator)**.** *To prevent a minority of authoritative learners from dominating the consensus results, introduce the equity indicator of opinion adoption:*

$$FI(t) = 1 - \frac{Gini(a(t))}{Gini_{max}} \quad (6)$$

Here, a(t) = [a_1 (t),. . ., a_n (t)] is the vector of the proportion of learner opinions adopted, Gini coefficient, and Gini max is the maximum possible Gini coefficient.

2.4. Formal Description of the Problem

Based on the above modeling, the problem of achieving consensus among collaborative adult education groups can be formally described as follows.

- Problem P1 (multi-objective consensus optimization problem)

$$\begin{array}{ll} \underset{\{o_i(t)\}}{max} & F(O(t)) = [F_1(O(t)), F_2(O(t)), F_3(O(t))] \\ s.t. & F_1(O(t)) = CR(t) \geq \delta_{th} \\ & F_2(O(t)) = FI(t) \geq \phi_{th} \\ & F_3(O(t)) = -\sum_{i=1}^{n} \| o_i(t) - o_i(0) \|_2 \\ & o_{ij}(t) \in [0,1], \forall i,j \\ & W(t) \in W_{feasible} \end{array} \quad (7)$$

$F_1(O(t))$: Represents the consensus rate of the group at time t.

$F_2(O(t))$: Represents consistency at time t.

$F_3(O(t))$: Represents a measure of the magnitude of change in opinion.

$O(t)$: Represents the opinion matrix of the entire group at time t, which is the viewpoint state of all learners at time t.

$o_i(t)$: The optimization variable is precisely this opinion matrix, with index i representing the i-th learner.

$o_{ij}(t)$: The jth viewpoint component of the i-th learner in O (t) (such as the degree of inclination towards a certain topic or the jth dimension in the opinion vector).

δ_{th}: The consensus rate threshold, which is the bottom line that the level of group consensus must reach.

ϕ_{th}: Consistency indicator threshold, which is the lower limit that consensus quality/group consistency must reach.

$CR(t)$: Maximizing consensus level.

$FI(t)$: Maximizing Consistency Index.

$W(t)$: Represents weight.

3. Optimization Algorithm

GCAOA adopts a four-stage iterative architecture of perception, learning, optimization, and regulation, as shown in Figure 1.

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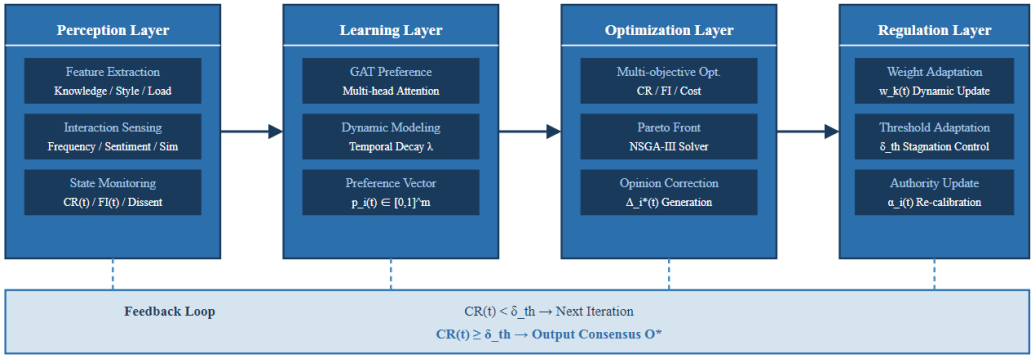


Figure 1. Overall framework of GCAOA. An asterisk marks the optimized outputs: $\Delta_i^*(t)$ denotes the opinion-correction output of the optimization layer, and O* denotes the final group opinion matrix returned by the algorithm.

The pseudocode description of the algorithm's main loop is as follows (Algorithm 1).

Algorithm 1. Pseudocode of the GCAOA main loop.

Input: learner group L, initial opinion matrix O (0), maximum iteration count Tmax
Step 1: Initialize feature matrix F and collaborative learning graph G (0)
Step 2: Calculate the initial authority vector α
Step 3: t ← 0
Step 4: while CR(t) < δ_th and t < T_max do
Step 5: Update the collaborative learning graph G (t) ← Perception module (collaborative learning log)
Step 6: Learning Preferences P (t) ← GAT Module (G (t), F, O (t))
Step 7: Solve the multi-objective optimization problem P1 → Generate correction suggestions Δ (t)
Step 8: Apply adaptive adjustment → Update parameters (δ _th, φ _th, α)
Step 9: Update the opinion matrix O (t+1) ← O (t)+η (t) •Δ (t)
Step 10: t ← t + 1
Step 11: end while
Step 12: O* ← O(t), t* ← t
Step 13: return O*, t*

The Graph Attention Network (GAT) preference-learning-module takes the collaborative-learning graph G(t) as input and learns the latent preference vector of each learner. The attention coefficient from node to node is calculated as follows:

$$e_{ij} = LeakyReLU(a^T[W^{att}h_i \| W^{att}h_j]) \quad (8)$$

After, softmax normalization is conducted as:

$$\alpha_{ij} = \frac{exp(e_{ij})}{\sum_{k \in N(i)} exp(e_{ik})} \quad (9)$$

α_{ij}: Normalized attention coefficient.
e_{ij}: Unnormalized attention score, reflecting the original matching degree of elements.
$N(i)$: The set of neighbors of element i, which includes all associated elements within its consideration range (such as all pointed nodes).

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After passing through L layers of GAT, the preference vector of learner li is mapped by the fully connected decoder from the final hidden layer representation:

$$p_i(t) = Sigmoid\left(W^{dec} h_i^{(L)} + b^{dec}\right) \in [0,1]^m \quad (10)$$

i: Indicates the i-th learner.

t: Number of iterations.

Sigmoid (·): Activation function.

W^{dec}: The weight matrix of the decoder.

$h_i^{(L)}$: The hidden representation vector obtained by learner i after passing through the L-th layer of the encoder.

b^{dec}: The bias vector of the decoder.

Figure 2 shows the structure of the GAT preference-learning module, demonstrating the process of multi-head attention aggregation and preference vector generation.

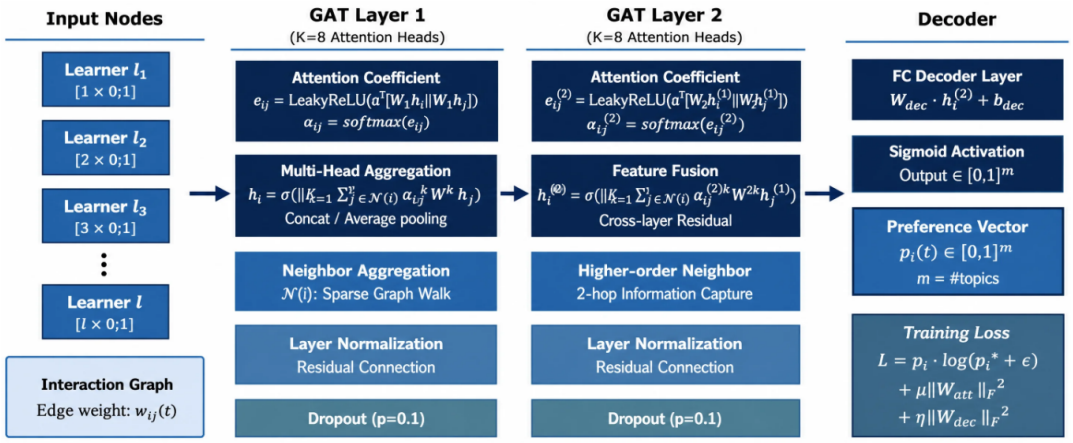


Figure 2. Structure of GAT preference-learning module. The superscript asterisk in p_i^* distinguishes the reference preference used in the training-loss expression from the current preference $p_i(t)$.

3.1. Adaptive Regulation Strategy

The adaptive adjustment strategy includes two sub-modules: weight adaptation and threshold adaptation (Figure 3), which jointly ensure the robustness of the algorithm in different scales and scenarios.

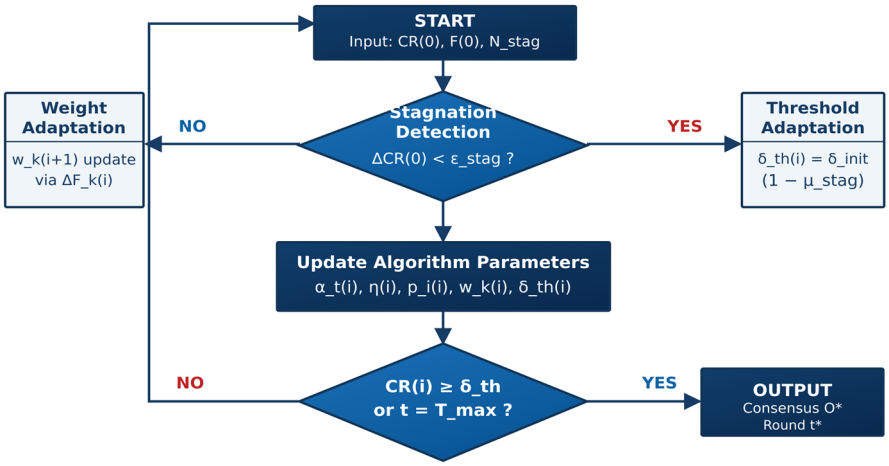


Figure 3. Adaptive adjustment strategy. The superscript asterisk identifies the outputs at termination: O* = O(t*) is the returned group opinion matrix, and t* is the iteration at which the algorithm terminates.

3.1.1. Weight

The weights of the objective function are dynamically adjusted on the basis of the current consensus progress rate:

$$w_k(t+1) = w_k(t) \cdot exp\left(\xi \cdot \frac{\Delta F_k(t)}{\sum_j \left|\Delta F_j(t)\right|}\right) \tag{11}$$

Here, $\Delta F_j(t) = F_k(t) - F_k(t-1)$ is the improvement of the k-th objective, and ξ is the sensitivity parameter for adjustment.

3.1.2. Threshold

When the progress of consensus reaches a long-term stagnation, the consensus threshold is dynamically lowered to avoid deadlock:

$$\delta_{th}(t) = \delta_{th}^{init} \cdot \left(1 - \mu_{stag} \cdot 1\left[\Delta CR(t) < \epsilon_{stag}\right]\right) \tag{12}$$

$\delta_{th}(t)$: The consensus threshold at time t. This value will dynamically adjust with the consensus status to determine whether the consensus meets the requirements.

δ_{th}^{init}: The initial set value of the consensus threshold, which is the benchmark threshold before dynamic adjustment.

$\Delta CR(t)$: The change in consensus progress, indicating whether there has been significant progress in the current consensus reaching process.

μ_{stag}: The stagnation penalty coefficient.

ϵ_{stag}: The stagnation judgment threshold.

4. Experiments and Results

All experiments were run on servers equipped with Intel Xeon Gold 6248R processors (3.0 GHz; Intel Corporation, Santa Clara, CA, USA) and an NVIDIA A100 graphics processing unit (80 GB of video memory; NVIDIA Corporation, Santa Clara, CA, USA), running Ubuntu 20.04 LTS (Canonical Group Limited, London, UK). We conducted experiments using three datasets (Table 2).

Table 2. Basic statistical information of the datasets.

Dataset	Type	Number of Learners	Number of Topics	Number of Collaborative Learning Records	Consensus Achievement Rate (Baseline)
CAE-Sim	Simulation	10–50	10	~45,000	—
MOOC-forum	Real-world	1847	48	12,653	78.3%
Corporate-learning	Real-world	634	15	8921	82.1%

- Computer-aided engineering simulation (CAE-Sim) dataset: Synthesized according to the § 2 modeling framework, including 5 sets of collaborative learning scenarios of different scales, generating a total of 2500 experimental samples;
- Massive Open Online Course (MOOC) forum (real dataset 1): Collected from the discussion forums of 5 adult continuing education courses on a large MOOC platform in China from September 2023 to August 2024;

- Corporate learning (real dataset 2): Based on the online collaborative learning records of a large enterprise's internal training platform for the whole year of 2024, this dataset provides authentic expert-annotated consensus results.

Comparison of Consensus Reaching Effectiveness

We compared GCAOA with the following four baseline methods, as shown in Table 3. GCAOA achieves optimal performance on all datasets, with a success rate of up to 93.7% in CAE-Sim scenarios, which is 14.8 percentage points higher than the suboptimal graph neural network-based change detection (GNN-CD). As the group size increases, the consensus achievement rate of GCAOA does not decrease but increases (90.2 to 93.7%), owing to GAT's excellent information aggregation ability on large-scale graphs, which verifies the scale robustness of this method.

Table 3. Comparison of consensus achievement rates of various methods on three datasets.

Method	CAE-Sim (1)	CAE-Sim (2)	MOOC-Forum	Corporate-Learning	Average
Majority Voting (MW)	71.2 ± 3.1	63.8 ± 4.2	74.1 ± 2.8	77.3 ± 2.3	71.6
Fuzzy Linguistic Quantifier (FLQ)	76.4 ± 2.8	68.5 ± 3.7	79.2 ± 2.4	81.6 ± 2.1	76.4
Social Network Analysis for Consensus Detection (SNA-CD)	81.3 ± 2.4	74.2 ± 3.1	83.7 ± 2.1	85.4 ± 1.9	81.2
graph neural network-based change detection (GNN-CD)	84.7 ± 2.1	78.9 ± 2.8	86.3 ± 1.8	88.1 ± 1.7	84.5
group consensus achievement optimization algorithm (GCAOA)	90.2 ± 1.7	93.7 ± 1.4	91.6 ± 1.5	93.2 ± 1.3	92.2

Figure 4 shows that the consensus achievement rate of each method varies with the size of the group, with GCAOA showing the most stable and consistently leading performance as the size increases.

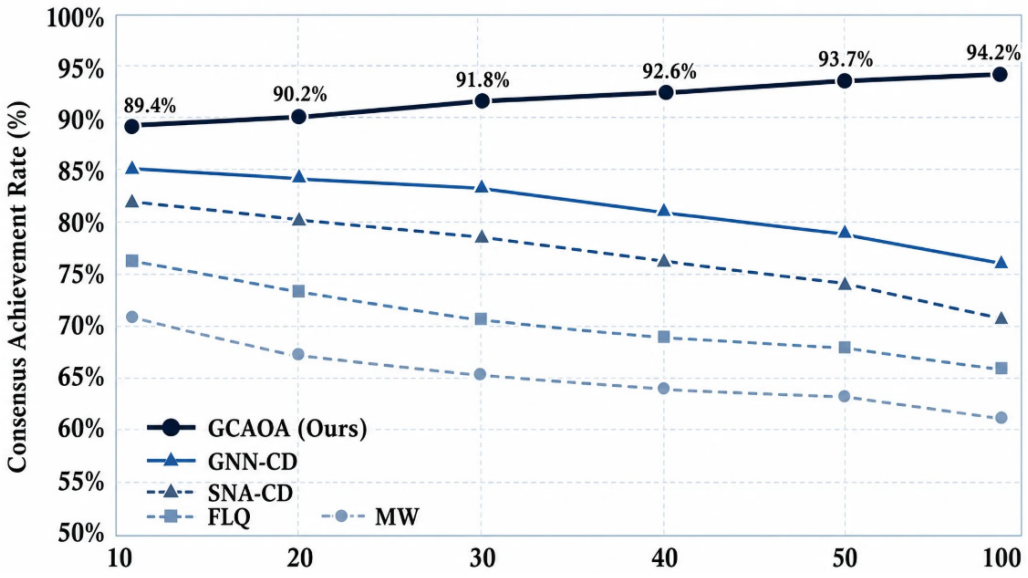


Figure 4. The curve of consensus achievement rate of each method as a function of group size.

The single computation time of GCAOA increases approximately O (n1.7) with the population size, which is significantly better than the O (n2) or even O (n3) complexity of traditional methods based on full pairwise comparison matrices (Table 4).

Table 4. Performance and computational overhead of GCAOA in different scale scenarios.

Group Size (*n*)	Consensus Achievement Rate (%)	Average Convergence Iterations	Total Computation Time (s)	Memory Usage (mb)
10	89.4 ± 2.1	12.3	0.98	142
20	90.2 ± 1.7	14.7	2.79	287
30	91.8 ± 1.5	16.2	5.99	521
40	92.6 ± 1.4	17.1	10.94	896
50	93.7 ± 1.4	17.5	17.15	1384
100	94.2 ± 1.2	18.3	57.10	4721

5. Discussion

We verified the effectiveness of GCAOA in collaborative adult education scenarios from both theoretical and experimental perspectives. This study compared the performance differences between GCAOA and GNN-CD. Upgrading from a static graph convolutional network to a dynamic GAT resulted in an average consensus achievement rate improvement of 7.7%, indicating that in adult education scenarios, the temporal evolution characteristics of learner preferences cannot be ignored. Attention mechanisms can effectively distinguish the differences in the importance of information from different neighbors, thereby more accurately analyzing preference dynamics. The current model mainly deals with discussion records in text form. In the future, research can explore upgrading the current rule-driven adaptive adjustment strategy to a learning-based intelligent adjustment strategy. Through continuous collaborative learning with the learning environment, the optimal adjustment strategy can be automatically discovered, further enhancing the algorithm's autonomous adaptability.

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